UNIVERSITY OF JOHANNESBURG

Sensitivity and specificity of Computer Aided Detection for scoring chest X-rays compared with Medical Panel in Johannesburg, South Africa

A research proposal presented to the

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In partial fulfilment of Master of Public Health

By

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DECLARATION

I, Kgaugelo Moropane hereby declare that the work on which this dissertation is based is my own work except where acknowledgements indicate otherwise. It is being submitted for a degree of Master of Public Health at the University of Johannesburg. It is not being submitted for any other degree or examination at any other university or learning institutions.

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Kgaugelo Moropane   Date: 12/03/2021

DEDICATION

I’m dedicating this work to my late grandmother and my late mother whom their spirit lives in me and they will remain in my heart forever. I further dedicate this work to my family, Sindisiwe Mazibuko, Botlhale Moropane, Thapelo Moropane and Lineo Moropane. Your support through the sleepless even when I’m absent from important events of your lives kept me going on. I love you so much guys. Your presence in my life makes this possible. Lastly, I dedicate the work to all the ex-mine workers who risked their lives working in mining activities with high risk of exposure to hazardous substance while striving to improve the economy of our country.

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Abstract

Background: Silicosis is one of the occupational diseases which increase with the duration of exposure to silica dust that has been a major problem for ex-miners. Chest radiograph is a valuable tool for diagnosing silicosis of ex-miners. Recently, artificial intelligence Computer Aided Detection (CAD) use in chest X-ray has gained momentum in medicine for diagnosing chest pathologies.

Aim and methods: The aim of the study was to determine the sensitivity and specificity of CAD software for scoring chest X-ray of ex-miners compared to Medical Panel in Johannesburg, South Africa. This was assessed using a quantitative, cross sectional study design. The study was conducted in Gauteng Province in the City of Johannesburg, Braamfontein. The study participants were from the Eastern Cape and North West provinces. Ethical clearance was obtained from the University of Johannesburg Faculty of Health Sciences Research Ethics Committee. Data collection clearance was obtained from the Medical Bureau of Occupational Diseases (MBOD). Data were collected from a sample of 295 participants using a structured questionnaire. Data analysis was performed using Statistics Package for Social Sciences (SPSS ver. 26) by comparing CAD4silicosis and CAD4TBv6 scores for each chest X-ray as an index test with the Medical Panel as the existing diagnostic test.

Results: CAD4Silicosis produced an Area Under Curve (AUC) of 0.918 (95%, CI 0.887 – 0.949) *p* value .000 to differentiate between silicosis and normal**.** When using CAD4Silicosis to score for combined silicosis and tuberculosis (TB) to differentiate between silico-TB and normal, the AUC was .802 (95%, CI 0.749 – 0.855) *p* value of .000. **Conclusion:** The CAD systems performed better across the scoring of silicosis, TB and silico-TB when compared to Medical Panel in differentiating between chest X-rays with TB, silicosis, and silico-TB. Furthermore, the findings demonstrate for the first time that CAD accurately separate combined silicosis and TB.

Key words:

Sensitivity and specificity, Computer Aided Detection (CAD), Silicosis in Ex-miners

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List of abbreviations

Abbreviation	Explanation
AI	Artificial intelligence
BME	Benefit Medical Examination
CAD	Computer Aided Detection
CCOD	Compensation Commissioner of Occupational Disease
DoH	Department of health
MBOD	Medical Bureau of Occupational Diseases
NIOSH	National Institution for Occupational Safety and health
ODIMWA	Occupational Diseases in Mines and Works Act (Act 78 f 1973)
SA	South Africa
STATSSA	South African Statistics
SPSS	Statistics Package for Social Science
TB	Tuberculosis
WHO	World Health Organisation
NIOSH	National Institution for Occupational Safety and health

Definitions of terms

Term	Definition
CAD4TB	Computer aided detection for tuberculosis
CAD4Silicosis	Computer aided detection for silicosis
CE certification	Mark that indicates conformity with health, safety and environmental protection standards
Chest X-ray	X-ray of the thoracic cavity to demonstrate the lungs
Ex-miner	A retired person who used to work at the mine
ODMWA	Occupational Diseases in Mines and Works Act of 1973 (ODMWA)
Pneumoconiosis	Inflammation and irritation of the lungs caused by deposition of dust and other small particles.
Silicosis	Lung disease which develops after prolonged exposure to silica dust
Tuberculosis	Infection of the lungs by mycobacterium tuberculosis bacteria

CHAPTER 1 INTRODUCTION

1.1 Introduction

Silicosis is one of the occupational diseases which increases with the duration of exposure to silica dust that has been a major problem for ex-miners (Fernandez *et al.*, 2015). Silicosis is defined as diffusion of pulmonary interstitial disease characterised by fibrotic changes in the lung parenchyma caused by continuous inhalation of silica dust during mining activities. It is one of pneumoconiosis disease which has no effective treatment available (Fernandez *et al.*, 2015).

Chest radiograph is an important tool for diagnosing silicosis of ex-miners. Chest radiographs involves the process of using an X-ray camera to capture the image (Williams, 2006). Chest radiographs are complex imaging which require a radiologist or clinicians trained in reading and reporting X-rays to provide a diagnosis (Woznitza *et al.*, 2018). Radiologists who are medical doctors trained for reading, interpreting and making a diagnosis from X-rays interpret chest X-rays images based on training received from medical school which lead to different radiologists interpreting a similar chest X-ray image differently. This has opened a room for the introduction of diagnostic tool for chest X-rays, computer aided detection (CAD) (Oliveira *et al.,* 2008).

1.1.1 Diagnostic tool

Diagnostic tool provides the ability to determine the presence or absence of a disease. A diagnostic tool is validated by comparing the tool's result against the gold standard or reference standard (Wong and Lim, 2011). The potential to discriminate between having a disease and not can be quantified by measuring the performance of the tool by determining its sensitivity and specificity with the area under curve (AUC). Sensitivity quantifies the ability of the diagnostic tool to correctly classify the proportion of ex-miners with silicosis, Tuberculosis (TB), silico-TB or other diseases. Specificity is the ability of diagnostic tool to correctly classify ex-miners without silicosis, TB, silico-TB or other diseases. The diagnostic tool is further measured through its predictive values. Positive predictive value classifies the diagnostic tool to predict ex-miners with the probability of having silicosis in ex-miners with positive result. Negative predictive value classifies the diagnostic tool to predict ex-miners with the probability of not having silicosis in ex-miners with negative result. Likelihood ratios are also used to measure the diagnostic tool. Likelihood ratio describes the proportion of expected test result from ex-miners with silicosis to those without silicosis (Šimundić, 2008).

Computer aided detection (CAD) is a computer software trained with thousands of chest radiographs in order to discriminate between normal and abnormal chest radiographs on the spot without a radiologist intervention (Oliveira *et al.,* 2008). CAD systems have been considered to maintain consistence and minimisation of errors in the interpretation of chest radiographs (Horvath *et al.*, 2010). The CAD systems are not meant to replace the radiologist, but to serve as a solution for areas with minimal resources that cannot access radiologist services (Chan and Siegel, 2018).

1.2 Background

Occupational lung diseases were recognised in South Africa as back in 1912 with silicosis and Tuberculosis (TB) as the standout occupational lung diseases (Pardesi, 2016). The prevalence of silicosis amongst goldminers in South Africa is estimated to be 18.3 – 19.9% (Churchyard *et al.*, 2015). A program to help ex-miners claim for silicosis and other occupational lung diseases was employed by the Department of Health (DOH) Directorate of Occupational Health and Compensation with Medical Bureau for Occupational Diseases (MBOD) and Compensation Commissioner for Occupational Diseases (CCOD) as the administrators for the program (Pardesi, 2016).

The program through the Occupational Diseases in Mines and Works Act (ODMWA) of 1973 provides compensation of silicosis and other occupational lung diseases for ex-miners (Mokwena, 2018). The MBOD is responsible for the provision of Benefit Medical Examinations (BME) services which includes chest X-ray and the certification of compensable occupational diseases including silicosis through the Certification Committee for ex-miners. There is approximately 1, 6 million ex-miners eligible for a BME and chest X-ray for the compensation process (Pardesi, 2016).

In the recent years artificial intelligence and machine learning has become an important topic in research bringing so many changes in the field of medicine, especially radiology (Oliveira *et al.*, 2008). Machine learning was discovered in 1962 when Arthur Samuel taught a computer to play a game of checkers against him (Phillipsen, 2019). Through multiple attempts of learning, the computer was able to beat a local champion on the game of checkers after it was trained with over thousands different techniques. In 1996 Delft medical system launched a grant to develop a machine learning software CAD4TB to analyse chest radiographs (Phillipsen, 2019). In 2001 an automated detection for TB in chest X-rays was published by Delft Medical Imaging and received a Conformity European (CE) certification in 2015 (Phillipsen, 2019). A Conformity European certification is mark that indicates conformity with health, safety and environmental protection standards (Halton, 2019).

To complement the chest X-rays imaging, artificial intelligence CAD has recently been used as a chest X-ray analysing tool to close up the gap of lack of human reader resources in the field of radiology and also to improve performance of diagnosis in medicine to minimize errors (Oliveira *et al.,* 2008). Computer aided detection are used by clinicians as a decision support for diagnosis (Patrick *et al.,* 2013) and to suggest diagnosis on the spot saving time for the radiologist from going through high volumes of radiographs in order to make a diagnosis (Oliveira *et al.,* 2008), in the case of the MBOD, a radiologist goes through 10 (ten) images in order to make 1 (one) diagnosis (Kistnasamy, 2019).

1.3 Problem statement

People working in mining activities are exposed to a multitude of hazardous substances which put them at high risk of developing prolonged respiratory diseases. Ex-miners are people who have been at high risk of being exposed to various type of harmful agents including silica dust during the working time in the mines (Mokwena, 2018). Due to the high risk of exposure to silica dust during their occupation, regular BME have been made available for all ex-miners who were considered to be at risk of being exposed to silica dust every two years according to the Occupational Diseases in Mines and Workers Act 78 of 1973 (ODMWA, 2011).

Chest X-rays are one of the essential diagnostic examinations conducted during BME. There is, however, a shortage of radiologists in South Africa with an estimate of 1.2 radiologist per 100 000 people in the population (Simpson, 2015) for making diagnosis in X-rays. This situation is also realised at the MBOD whereby there is one radiologist on part time basis producing reports for the chest X-rays conducted on the ex-miners. The shortage of human reader has contributed to delayed care and compensation leading to death or preventable morbidity.

Not all ex-miners who get a BME conducted are compensable. Only ex-miners whose diagnosis comes positive for an occupational lung disease from the BME are compensated based on the degree of impairment to their lungs (ODMWA, 2011). The degrees of impairment are categorised as follows, 0 to 10 degree non compassable impairment, 10 to 40 degree impairment, 1st degree compensation and >40 degree impairment, second degree compensation (ODMWA, 2011).

A new diagnostic test for detecting diseases in chest X-rays is now available but underutilized because its sensitivity and specificity for detecting occupational diseases is not yet known and there's not much information about it hence the need for this study.

The areas of studies which have been previously done on CAD systems have focused on sensitivity and specificity of CAD in detecting TB, comparison of CAD and radiologist, and Comparison of CAD with GeneXpert. Additionally, studies which have been previously conducted in ex-miners have not focussed on innovative tools to improve the efficiency of ex-miners BMEs for compensation

Currently there is only one scientific study that has been recently conducted using CAD system for diagnosis of silicosis.

1.4 Aim and Objectives

The aim of the study was to determine the sensitivity and specificity of computer aided detection software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa.

1.4.1 Specific objectives

1. To determine the sensitivity and specificity of CAD for detecting silicosis
2. To determine the predictive values of CAD for detecting silicosis
3. To determine likelihood ratios of CAD for detecting silicosis
4. To compare the performance of CAD with the Medical Panel in scoring for silicosis

1.5 Research question

The overall research question is, what is the sensitivity and specificity of computer aided detection software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa?

1.5.1 Specific research questions

1. What is the sensitivity and specificity of CAD for detecting silicosis?
2. What are the predictive values of CAD for detecting silicosis?
3. What are the likelihood ratios of CAD for detecting silicosis?
4. What will be the differences between CAD and Medical Panel in scoring for silicosis?

1.6 Research Hypothesis

The study sought to determine the sensitivity and specificity of computer aided detection software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa. Below is the null and alternative hypothesis

H_0: CAD software will not sensitively and specifically score chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa.

H_1: CAD software will sensitively and specifically score chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa.

1.6.1 Specific hypothesis

1. **To determine the predictive values of CAD for detecting silicosis**

   H_0: CAD will incorrectly determine positive and negative predictive values for detecting silicosis

   H_1: CAD will correctly determine positive and negative predictive values for detecting silicosis

2. **To determine likelihood ratios of CAD for detecting silicosis**

   H_0: CAD will incorrectly determine likelihood ratios for detecting silicosis

   H_1: CAD will correctly determine likelihood ratios for detecting silicosis

3. **To compare the performance of CAD with the Medical Panel in scoring for silicosis**

   H_0: There will be different scoring between CAD and Medical Panel assessment in counting for silicosis

   H_1: There will be similar scoring between CAD and Medical Panel assessment in counting for silicosis

1.7 Feasibility

The study focused on ex-miner’s population estimated to be 1.6 million across the Southern African Development Community (SADC) region. The resources required to complete the study were available through self-funding and sponsorship. Sampling of participants was possible and could be done with ease having obtained permission to access archived data with relevant information to aide identification of eligible participants. These factors enabled the execution of the study in a timely manner.

1.8 Purpose and Importance of the study

The purpose of this study was to determine the sensitivity and specificity of computer aided detection software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa. For this purpose, CAD was defined as a software used to analyse a chest X-ray images for silicosis by generating a score between 0 and 100. Medical Panel (team of four doctors) was defined as the reference standard for diagnosing silicosis. The Medical Panel (team of four doctors) are the officials endorsed by the MBOD as certification committee responsible for certifying BMEs of ex-miners hence they are defined as a reference standard.

The study is important to help the MBOD implement effective systems which will help in the compensation process of ex-miners. Effective systems will ensure that ex-miners are compensated within 3 months after conducting BME. It is further important in addressing a backlog at the MBOD for separation of normal and abnormal chest X-rays images to ease the load from the Medical Panel. The study will further provide a guide for the mining sector to use innovative systems in future for diagnosing silicosis and other occupational diseases in the industry. Additionally, the study will contribute to the attainment of my master's degree in public health and improving my knowledge in the field of my work.

1.9 Significance of the study

The need to facilitate for timely compensation of ex-miners and ensure that they receive care within 90 days make this study urgent and important. The MBOD on ex-miner's compensation program requires evidence on the usefulness of this innovation to enable a faster processing to get help for the ex-miners. It would also facilitate for clearing of the currently existing backlog.

Further, the study will also contribute new knowledge and literature in the field of occupational health. It closes the gap that exists in literature for comparing CAD with Medical Panel of four experienced occupational health experts in South Africa. The findings of this study may assist in availing of new data of occupational disease and CAD which future studies can reference on to further enhance the profession. The overall findings will contribute to policy reinforcement for diagnosis of ex-miner population.

1.10 Delimitation

The research was conducted in the Braamfontein, Johannesburg South Africa. The scope of the research was limited to ex-miners and only those who had a BME file conducted for compensation purposes at the MBOD database. The sampled population was taken from the ex-miners BME files who submit BMEs between March and April 2020. The study used chest X-rays images which met all minimum chest X-rays quality standards. The study used only a posterior anterior chest X-ray conduced from the ex-miners, lateral or other additional chest X-rays views were not used in the study. The study used CAD systems which are CE certified and has been used in Southern African population base before with more than three peer reviewed scientific publications that supported the use of the CAD systems for detecting diseases in chest X-rays.

1.11 Summary and Transition

People working in mining activities are exposed to various types of hazardous substances which put them in high risk of developing prolonged respiratory diseases. Silicosis is one of the occupational diseases which increases with the duration of exposure to silica dust that has been a major problem for ex-miners. Due to the high risk of exposure to silica dust during occupation, regular BME should be available to all ex-miners who were at risk of being exposed to silica dust every two years according to the Occupational Diseases in Mines and Workers Act. Chest radiograph is an important tool for diagnosing silicosis of ex-miners. To complement the chest X-rays imaging, artificial intelligence CAD has recently been used as a chest X-ray analysing tool to close the gap of lack of human reader resources in the field of radiology and improve performance of diagnosis in medicine to minimize errors.

The aim of the study was to determine the sensitivity and specificity of computer aided detection software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa. The null hypothesis of the study stated that CAD software will sensitively and specifically score chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa, and the alternative hypothesis stated that CAD software will not sensitively and specifically score chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa. The study focused on ex-miner's population estimated to be 1.6 million across the Southern African Development Community (SADC) region. Findings of this study are important to help the MBOD implement effective systems which may help in the compensation process of ex-miners. Further, the study contributes new knowledge and literature in the field of occupational health. The study used a CAD system which is CE certified and has been used in Southern African population base before with more than three peer reviewed scientific publications.

CHAPTER 2: LITERATURE REVIEW

2.1 The theoretical framework

The study aims to determine the sensitivity and specificity of Computer Aided Detection software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa. From the literature search, there are multiple CAD systems which have been developed for commercial purposes available in the market. A theoretical framework of an automated and intelligence of CAD software for silicosis is purposefully applied.

The study applies the theory of artificial intelligence Limited Memory which is capable of learning from historical data to make a decision to determine the sensitivity and specificity of Computer aided detection software for scoring chest X-rays of ex-miners. The Limited Memory theory can store previous data and predictions, using that same data to make better predictions. This theory applies Reinforcement learning to make better predictions through many cycles of trial and error (Hintze, 2016). The developers of the CAD software continue to train the model with new data. Computer aided detection systems uses a deep learning and are trained with thousands of chest X-rays images stored in their memory to form a reference model for detecting diseases in the lungs based on the memories from previous validation. When a chest X-ray images is scanned by the CAD system, it uses the training images as reference to understand the contents of the image presented to it and based on the learning experience it label the new image with increasing accuracy.

2.1.1 Justification for using CAD

Computer aided detection is a software that uses deep machine learning techniques to automatically detect abnormalities in a chest X-ray (Murphy *et al.,* 2019). It is validated with multiple chest X-rays images in order to learn and detect lung diseases. Computer aided detection system extract characteristics of a chest X-ray images and use a classifier to measure abnormalities. Computer aided detection systems are usually assessed through receiver operative characteristics and region of interest. Computer aided detection are calibrated based on the sensitivity and specificity for detecting true positive and true negative for separation of normal and abnormal images. Computer aided detection can be validated to detect different kind of diseases however large volume of data for validation is required (Firmino *et al.*, 2016).

2.1.2 Description of the way CAD is used

The process of CAD for the study involved the following steps, uploading of the chest X-ray to the CAD software after image have been taken, image processing by CAD, normalising of the images to the software parameters, identification of suspicious location, classification of the abnormalities, scoring of the images from 0 – 100 which indicate the probability of having silicosis, TB, Silico-TB or other abnormalities and applying of heat maps for indicating areas of suspected abnormality shown in figure 2.1.

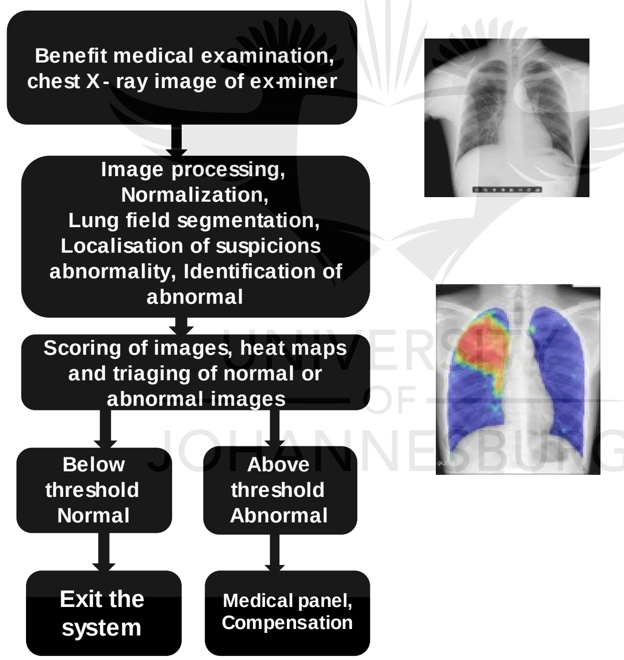


Figure 2.1. CAD scoring process

2.1.3 Relationship between CAD and Medical Panel

Silicosis is one of interstitial lung diseases caused by inhalation of dust particles or other chemicals at workplace which causes damages to the lungs. The disease appears at different stages which can accumulate over a long period of time. The severity of the disease is dependent upon the duration of exposure. The disease is more likely to be diagnosed in people who worked in mining activities. Different exposures result in different diseases such as silicosis which increase the susceptibility to TB. When an ex-miner is diagnosed with the silicosis, they are compensated as a result of exposure during their occupation. In order to be diagnosed, a Benefit Medical Examination inclusive of chest X-ray is conducted in order to make a diagnosis. Chest X-ray is a valuable examination for diagnosing silicosis with other clinical findings such as pre exposure history, clinical examination, and spirometer result. Due to process of delays in getting chest X-ray reports, the process of compensation takes over 503 days while the disease becomes more aggressive resulting in mortality of some cases before compensation is concluded (Weatherspoon, 2017).

The sensitivity and specificity of CAD is determined by its ability to detect true positive and true negative silicosis, TB, silico-TB and other occupational diseases. Computer aided detection is validated by comparing the scoring with the gold or reference standard for diagnosis of the diseases. In this study CAD was validated by comparing the CAD scoring of silicosis with the Medical Panel.

The Medical Panel is a team of four clinicians who hold a minimum qualification of Bachelor of Medicine and Bachelor Surgery specializing in occupational health with over 10 years' experience in the field of occupational diseases. The Medical Panel are certified as B readers by the National Institution for Occupational Safety and Health (NIOSH). The Medical Panel are further complemented by a radiologist. The radiologist has over 20 years' experience in diagnosing silicosis certified with a B reader by NIOSH. The Medical Panel and the radiologist are regarded as the reference standard for this study. The Medical Panel conclude a diagnosis with considerations of pre-exposure history, clinical assessment, GeneXpert result, and lung function test result shown in figure 2.2.

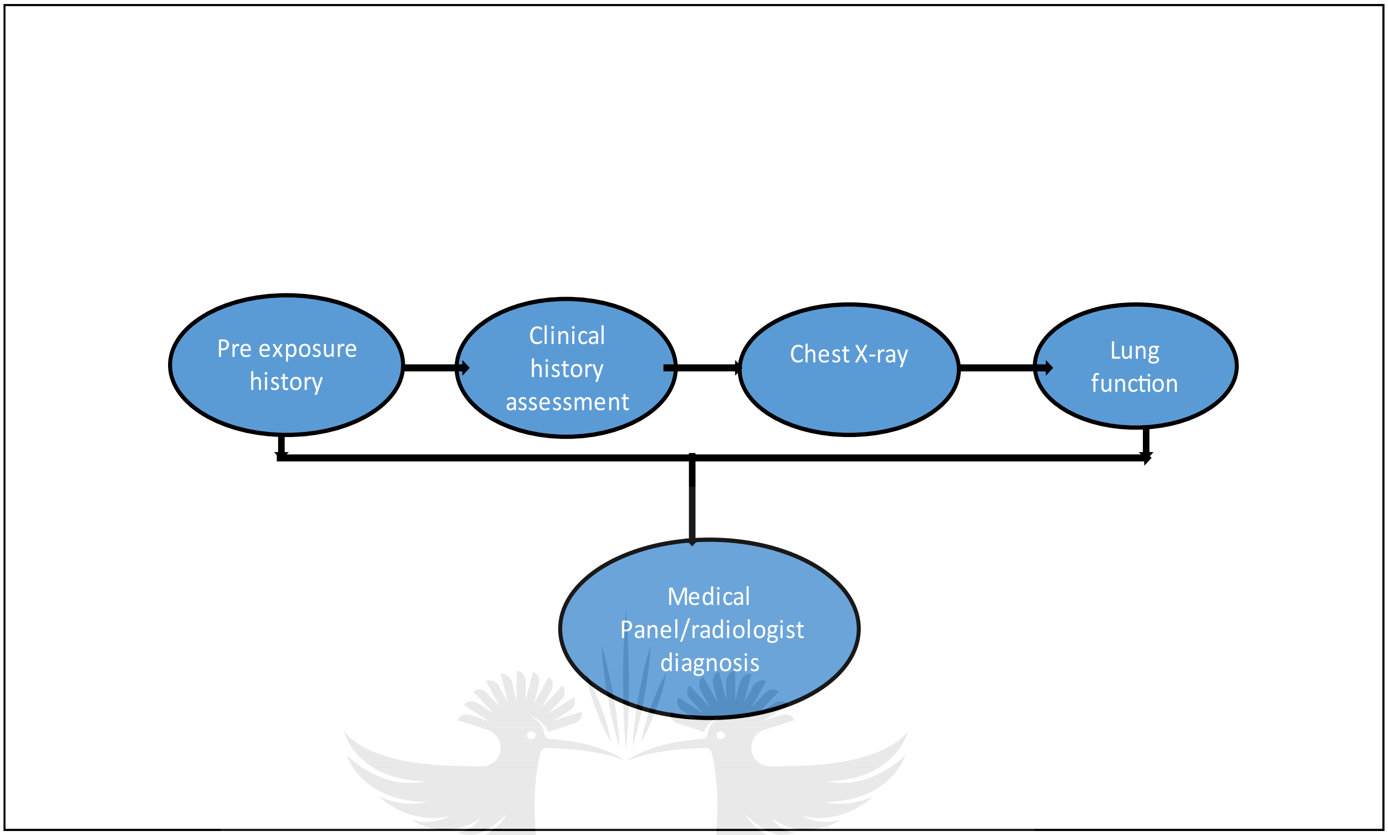


Figure 2.2. BME process flow

2.2 Literature review

2.2.1 Introduction

Recent developments in radiology have borne the availability of digital chest X-ray in mobile settings whereby even the under resourced areas have access to this essential diagnostic tool (Oliveira *et al.*, 2008). Chest X-rays are the most common scans that are used with artificial intelligence with over 2 billion performed worldwide annually (Li *et al.*, 2018). Due to the high volumes of chest X-ray images conducted daily in healthcare facilities, limited number of humans reading the chest X-rays is challenging in environment with limited resources (Retico, 2013). Further to this there are numerous diagnostic errors in chest X-ray reading from human readers who are inexperienced resulting in wasteful of resources, inefficiencies in workflow as well as long waiting time between the patient and the result. In the United Kingdom it was estimated that

330 000 X-rays have a waiting period of more than 30 day to get a report (RSNA, 2018). Machine learning systems have been proposed as a means to reduce the backlog by triaging all urgent cases to the front of the queue for radiological reporting (RSNA, 2018). This chapter provides a detailed literature search strategy, literature review of CAD systems and its impact in the field of medicine. It further highlights the gaps available in literature which informed the need for this study.

2.3 Literature search strategy

Several studies have been published on the use of artificial intelligence, computer aided detection and machine learning for detecting abnormal on chest X-ray (Computer-aided detection in chest radiography based on artificial intelligence: a survey by (Qin *et al.*, 2018), Computer-aided reading of tuberculosis chest radiography: moving the research agenda forward to inform policy by (Kahn *et al.*, 2017) and others). To understand the findings from the published data, literature was searched from academic databases namely, Google Scholar, PubMed, Science Direct, International journal of Tuberculosis and lung disease (IJTLD) and Organisation, and professional bodies (World Health Organisation (WHO), International labour organisation). The literature search used journal articles, investigated articles, researched thesis, reports from organisations such as WHO and government websites such as Department of Health (DOH) statistics. The search was scaled down to focus more on the literature published in the past five (5) years, although publications that were over five years were not completely left out. Key word used for the search are sensitivity and specificity, computer aided detection, artificial intelligence, chest X-ray and ex-miners. The combination search included artificial intelligence and chest X-ray, computer aided detection and chest X-ray, sensitivity and specificity and computer aided detection, Benefit Medical Examination and ex-miners, and ex-miners and compensation.

2.3.1 Computer Aided Detection

A literature search found that many studies indicate that CAD systems can be used to detect abnormalities from chest X-ray image. This was supported by Radiology Society of America (RSNA, 2018) who outline that an artificial intelligence system can be trained to successfully detect abnormalities from a chest radiograph. However, to get a machine to learn how to analyse chest X-ray images it requires a large amount of data to train with. In a study of using CAD for pneumonia, the artificial intelligence software outperformed a team of four radiologists with 112 000 chest X-rays images used to compare the software and the radiologists (Wang *et al.*, 2017).

Another study conducted in India found that an artificial intelligence software used to diagnose four different lung pathologies was as accurate as the radiologist (Singh *et al.*, 2018). This indicates that with availability of large enough dataset, CAD can be trained to diagnose different types of chest diseases.

A prospective double blinded randomised control trial study indicated that a deep learning algorithm could interpret X-rays images 150 times faster than a radiologist with 1.2 seconds versus 177 seconds (Topol, 2019), this was further supported by Qin *et al* (2018) who also indicated that CAD systems can reduce the workload of clinicians by reading high volumes of chest X-rays images in a short period of time. This indicate that CAD could be the solution for the MBOD with only one radiologist on a part time basis for diagnosing chest X-rays images. However, Topol (2019) indicated that artificial intelligence is still far from demonstrating high accuracy and reproducibility of machine learning in real world clinical environment. This shows that CAD systems cannot be used alone as a diagnosis tool alone, but rather a support or triage tool for the MBOD. Retico (2013) stated that CAD improves workflow efficiency although CAD performance needs to improve in order to detect small nodules in the lungs. At the MBOD, a backlog in chest X-rays is realised because each chest X-ray image must be assessed by the Medical Panel and a radiologist, however this literature demonstrates that CAD can improve efficiency by separating chest X-rays which must be assessed by the Medical Panel and the radiologist to improve efficiency in the process flow.

A study done in Pakistan found that CAD for tuberculosis (TB) in contrast with GeneXpert agreed on the diagnostics findings (Murphy *et al.*, 2019). Tuberculosis is one of the pneumoconiosis group of occupational diseases which is prevalent in ex-miners, this indicate that CAD systems can detect TB as one of the occupational diseases. A review by Khan *et al* (2017) on available CAD system found that evidence currently available from the literature suggest that CAD system can achieve high sensitivity of 85% plus, although specificity is as low as ranging between 23% to 69%. This informed the interest of the hypothesis to determine the sensitivity and specificity of CAD in detection silicosis and TB compared to Medical Panel for this study. Further to this, there are not enough studies which confidently estimate diagnostic accuracy in real time screening settings or field work activity. The review by Khan *et al* (2017) also highlighted that an ideal CAD system should be able to read images from a different population without changes in performance. The similar review found that CAD systems provide inaccurate results in different population groups. Qin *et al.*, (2019) emphasize that there's a need to conduct a specific pilot on population as using a universal cut-off thresholds of CAD systems result in different performance. These indicate that CAD systems must be validated against specific population groups of interest when deciding on cut-off thresholds to minimise errors. This has also informed the study to use a CAD system which has been validated with a Southern African population.

A multi-site evaluation of diagnostic accuracy of three deep learning system for detecting TB in Nepal and Cameroon found that all three CAD systems performed better than human readers with a higher Area Under Curve than most of the published literature of previous version of CAD. The study further indicated that there was no statistical difference amongst all the three systems in the Area Under Curve. It further found that all three systems had over 95% sensitivity with specificity going up to 80% (Qin *et al.*, 2019). This generally suggest that there have been improvements in CAD systems as they evolve.

2.4 Summary and Transition

Computer Aided Detection is a software that uses deep machine learning techniques to automatically detect abnormalities in a chest X-ray. The sensitivity and specificity of CAD is determined by its ability to detect true positive and true negative silicosis, TB, silico-TB and other occupational diseases. In this study CAD is validated by comparing the CAD scoring of silicosis with the Medical Panel. The Medical Panel and the radiologist were regarded as the reference standard for this study.

The study applies the theory of artificial intelligence Reactive Machines to determine the sensitivity and specificity of Computer Aided Detection software for scoring chest X-rays of ex-miners. The Reactive Machine theory have the ability to form memories and use past experiences to inform the current situation. A conceptual framework with the pathophysiology for the relationship between CAD and Medical Panel was explicated.

To understand the findings from previously published literature, a literature was searched from academic databases using sensitivity and specificity, computer aided detection, artificial intelligence, ex-miners and chest X-ray as key word. From the literature search many studies suggest the use of CAD in detecting different chest diseases. The studies further indicate that CAD have the potential to improve workflow process efficiency, especially in high volume diagnosis as well as areas with limited resources. The studies also find high sensitivity in detecting lung disease, although specificity is low which highlights the need for improvement. The studies further suggest more research to be conducted on CAD. It is further outlined that CAD should be adaptable for use in different population groups.

CHAPTER 3: METHODOLOGY

3.1 Introduction

The aim of the study was to determine the sensitivity and specificity of CAD software for scoring chest X-ray of ex-miners compared to Medical Panel in Johannesburg, South Africa. This chapter provides the description of the study design, study area, target population and associated sampling method. It further describes inclusion and exclusion criteria for the study. It details ethical considerations as well as reliability and validity of data.

3.1.1 Study Design

The study is a quantitative, cross sectional study design conducted to determine the sensitivity and specificity of CAD software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa using primary data from the MBOD.

3.1.2 Study area

The study was conducted in Gauteng province which consist of a population of 13 399 725 million people who make up 23% of the total South African population in the city of Johannesburg, Braamfontein (Stats, 2019). The province is made up of 6 189 875 males and 6 082 388 females. It consists of 77.4% Black African, 15.6% White, 2.9% Asian, 3.5% coloured people and 0.7% other group. The most common spoken language is Zulu 20%, followed by English 13.6%, Afrikaans 12.6%, Northern Sotho 10.7%, Tswana 9.2%, Sotho 11,7%, Xhosa 6.7%, Tsonga 6,7%, Venda and other languages 6%. The city of Johannesburg is the metropolitan municipality with a population of 4 949 347 million people.

The study participants were from the Eastern Cape (Alice and Bizana outreach) and North West (Stillfontein outreach) provinces. The Eastern Cape is estimated to have a population of 6 996 97. The Eastern Cape is divided into two metropolitan municipalities (Buffalo City Metropolitan Municipality and Nelson Mandela Bay Metropolitan Municipality) and six district municipalities. The main language spoken is IsiXhosa. The province is estimated to have 73% of ex-mine workers from the estimated 1,6 million. The North West province has a population of 3 748 436. North West is divided into four district municipalities (Bojanala Platinum District, Ngaka Modiri Molema district, Dr Ruth Segomotsi Mompati district and Dr Kenneth Kaunda district). The most spoken language is Setswana. The North West is estimated to have 37,8% person working in the mines form the mining population data.

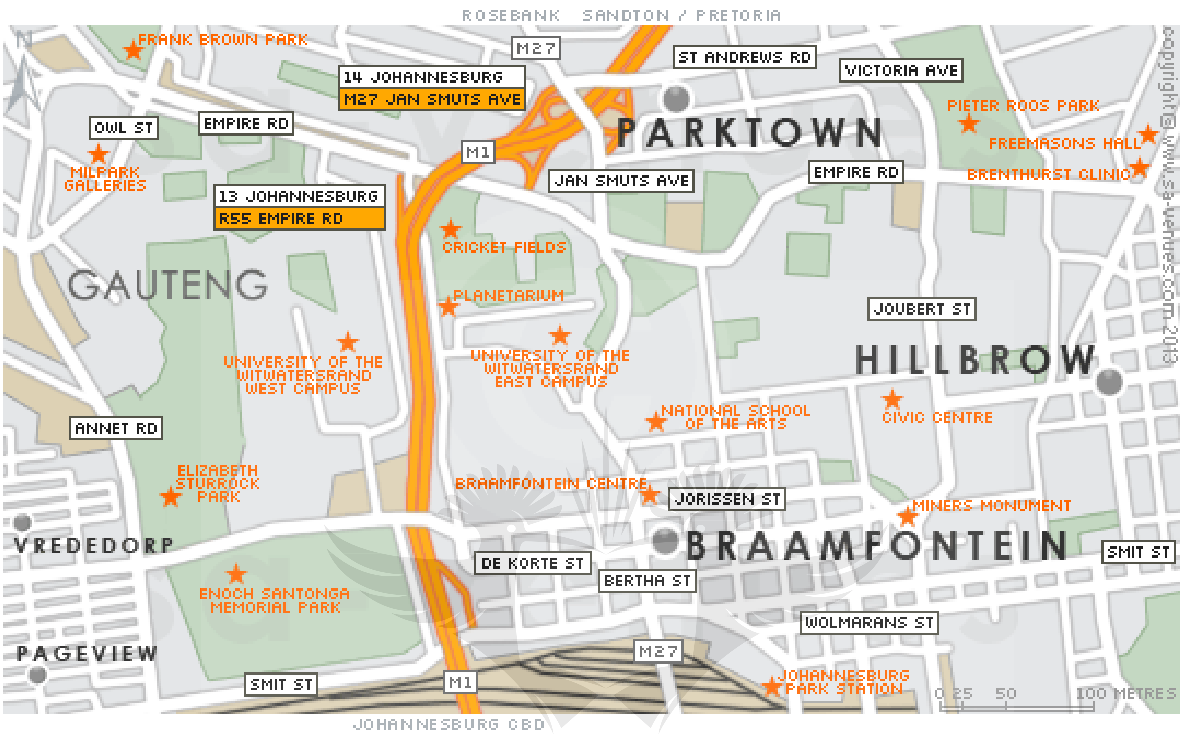


Figure 3.1. MBOD Braamfontein map

3.1.3 Target population

The target population for the study were ex-miners. There were approximately 1, 6 million ex-miners in the Southern African Development Communities (SADC) region in 2019. About 73% of ex-miners originate from South Africa, from the 73%, 31% are estimated to be from the Eastern Cape. About 12% of the ex-miners are estimated to be from Lesotho, Mozambique is estimated to have 9% of the ex-miners while Swaziland, Botswana, Malawi are estimated to have 2% respectively with 0.1% from other countries.

3.1.4 Study population

The study population comprised of ex-miners from various catchment areas of the Eastern Cape and North West provinces. The ex-miners presented to One Stop Mobile outreaches to get a BMEs conducted for compensation purpose. The BME files and the chest X-rays images are submitted to the MBOD in Braamfontein where the study was conducted for assessment by Medical Panel for compensation purposes. The population from Eastern Cape and North West provinces are the two provinces which submitted BMEs files to the MBOD during data collection period for the study.

3.1.5 Study variables

The study variables were grouped into two sections, section one consisted of socio demographics characteristics with a unique identifier given for each participant, gender, province and examination centre. Section two consisted of clinical information. The variables were coded as categories of 1 = positive, 2 = negative. The variables consisted of diagnostic quality, Medical Panel abnormal, Medical Panel silicosis diagnosis, Medical Panel TB diagnosis and Medical Panel silico-TB diagnosis. It further had CAD4Silicois and CAD4TB score as a continuous variable. See table 3.1.

Table 3.1: Study variables

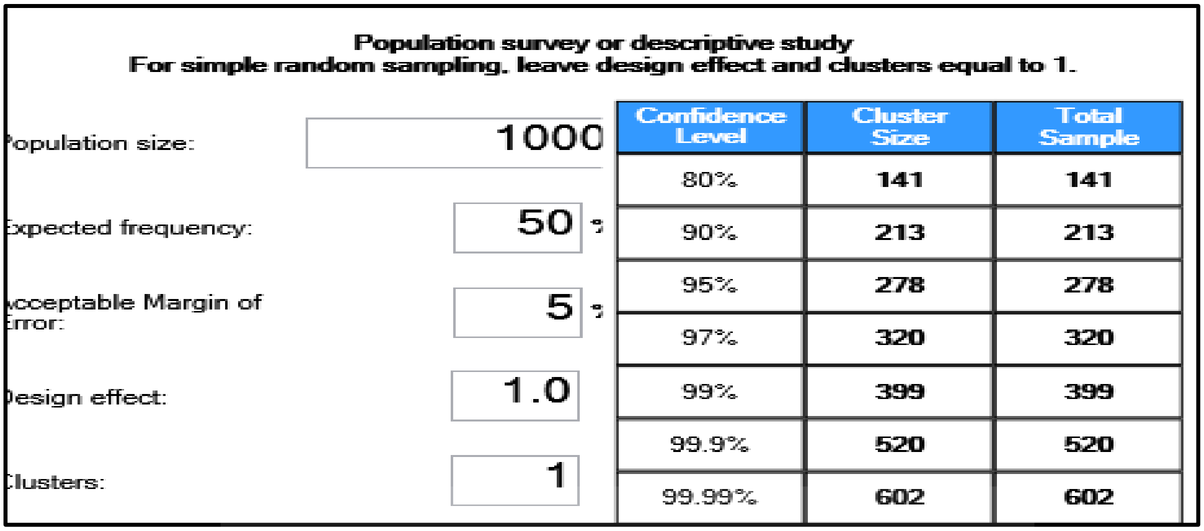
Section A		
Sociodemographic		
Age		
Gender	Male: Female:	1 2
Race	Black: White: Coloured: Asian:	1 2 3 4
Province		
Examination centre		
Section B		
Clinical information		
Diagnostic quality of the chest X-rays	Yes: No:	1 2
Medical Panel Diagnosis / Radiologist		

Chest X-ray normal or abnormal diagnosis	Positive: 1 Negative: 2
Chest X-rays silicosés diagnoses	Positive: 1 Negative: 2
Chest X-ray TB diagnosis	Positive: 1 Negative: 2
Chest X-ray combined silicosis and tuberculosis diagnosis	Positive: 1 Negative: 2
Computer Aided Detection Scoring	
CAD4Silicosis score	
CAD4TB score	

3.2 Sampling and Sample Size

The study applied a non-probability convenient sampling by selecting BMEs files with a chest X-rays of ex-miners submitted to the MBOD for assessment and certification by Medical Panel between March and April 2020. All BME files submitted for assessment by the Medical Panel during that period were regarded as a sample for the study. The BME files were submitted to the MBOD from different One Stop Centres or mobile outreaches after a BME has been conducted for the certification committee to assess the files with a chest X-ray to diagnose silicosis and other occupational diseases for compensation. The chest X-rays images are uploaded to the cloud server which was accessible at the MBOD through credentials.

The sample size was estimated using the Centres for Disease Control and EPINFO program for a population survey shown in figure 3.2.



Population survey or descriptive study
For simple random sampling, leave design effect and clusters equal to 1.

opulation size:	1000
xpected frequency:	50
cceptable Margin of rror:	5
esign effect:	1.0
lusters:	1

Confidence Level	Cluster Size	Total Sample
80%	141	141
90%	213	213
95%	278	278
97%	320	320
99%	399	399
99.9%	520	520
99.99%	602	602

Figure 3.2. Sample Size Estimation Using EPINFO 7.2

There were approximately 500 BMEs files of ex-miners submitted to the MBOD from the One Stop centre or mobile outreaches for compensation monthly during the study. The sample size was estimated at 278 at 95% confidence level with 25% contingency estimated based on 1000 files of ex-miners submitted during data collection of two months period.

3.2.1 Inclusion criteria

The study included all ex-miner BME files, male and female participants who were 18 years and older of all races, educational, socio-economic status and residential background who had a BME conducted and submitted to the MBOD for compensation purposes between March and April 2020 who came from the Eastern Cape (Alice and Bizana outreach) and North West (Stillfontein outreach) province. Participant BME files had a unique industry number which is an identifier for each ex-miner that is used to trace environmental exposure history and link it with all ex-miner's information including biometrics. The industry number is embraided in the X-ray images for linking up results.

3.2.2 Exclusion criteria

Miners who are actively working in the mining industry were excluded from the study since they have access to BMEs at their work environment and can submit claim through the employer. BME files which were not part of the ex-miner's database from the MBOD were excluded in the study. Ex-miner BME files who are differed due to missing documents in the BME files were excluded since they could not be certified. Poor quality chest X-rays images which did not meet all standard quality for reporting were excluded. BME files with missing chest X-ray image and diagnosis from the Medical Panel were excluded.

3.3 Data collection

3.3.1 Data collection instrument

The study used a structured questionnaire as a data collection instrument for collecting fresh data which have never been used before. The questionnaire was applied in English language since the information in the BME file were recorded in English. The questionnaire was divided into two sections of socio demographics and clinical information See **Appendix 1.**

3.3.2 Instrumentation

CAD4Silicosis version 1 and CAD4TB version 6 software's were applied from the pilot until the duration of the study. A standardised cut off threshold for scoring chest X-ray's image with features of silicosis and TB were set via the Area Under Curve closer to the coordinate's points throughout the study. The CAD systems at the latest versions were calibrated and validated based on manufacture guidelines.

3.2.3 Role of the CAD4Silicosis and CAD4TB developer into the study.

The CAD4Silicosis and CAD4TB developer had no role in the study. The developer only processed anonymised chest X-rays images for scoring by the software. The developer had no role in study design, data collection, data analysis or writing up of the result and had no access to Medical Panel finding and radiologist outcome.

3.4 Data analysis / statistical analysis

Data analysis process included the use of IBM SPSS Statistics 26 analysis software by objective through comparing CAD system as an index test and Medical Panel as the existing diagnostic test with the radiologist as a reference standard. The software package is a comprehensive software used for data entry, data coding and recording, data analysis and hypothesis testing. The first component report on descriptive statistics using frequencies and percentages on the dependent and independent variables presented in tables and figures including sociodemographic characteristics. The other components report on sensitivity and specificity, Predictive values, Likelihood ratios, Receiver Operator Curve (ROC) and Area Under Curve (AUC) for the research questions at *p* value of 0.001.

The sensitivity and specificity of CAD was determined by making a 2X2 table for categorising ex-miner with silicosis and TB, and ex-miner without silicosis and TB against the Medical Panel assessment and the radiologist as the refence standard through analysis by objective at *p* value of 0.001.

3.5 Reliability

In order to measure the extent in which the study produce results which are reliable and reproducible, the study employed a research assistant who assisted in data collection and capturing which were further validated by the researcher in order to minimise errors. The research assistant was trained for applying questionnaires two weeks prior data collection and had enough time to understand the process. She was further a part of the pilot to apply the questionnaire in practice. CAD4Silicosis Version 1 and CAD4TBv6 of the software was applied from the pilot until the end of duration of the study. The CAD4Silicosis Version 1 and CAD4TBv6 software have been validated with thousands of X-rays images for detecting diseases in chest X-rays. The CAD systems used a score from 0 to 100. A standardised cut-off threshold closer to the coordinate point summarised by the AUC was applied where required during analysis throughout the study. Reliability was further tested by running frequencies and classifiers which produced similar output under the similar conditions.

3.6 Validity

For testing of validity to ensure accurate scoring of the chest X-rays, a pilot study was conducted at the Minerals Council of South Africa where the questionnaire was applied to fifth teen (15) BME files of the participants. The preliminary outcome of the pilot served as a baseline to apply the instruments for conducting the actual study. Parameters of the CAD systems were kept the same throughout the study.

3.7 Pilot study

3.7.1 Introduction

A pilot study is an essential stage of the research to provide groundwork of the research proposal for testing of feasibility of the study, the recruitment of the participants, the data collection instruments, and the data analysis (Hassan *et al.*, 2006). The purpose of the pilot for this study was to

- To determine the feasibility of the study and identify weaknesses
- To determine the practicability of recruitment of participants
- To test the data collection instrument and process
- To test preliminary analysis of the results.

3.7.2 Feasibility of the study protocol

A pilot of the study was conducted at the Minerals Council of South Africa in Johannesburg in March 2020. The Minerals council was selected because a team of four Medical Panel members of certification also chair there to assess Benefit Medical Examinations (BME) files for certification. The files assessed at the Minerals council resembled the types of participants used in the study since they are all ex-miners with BME files submitted for compensation purposes.

3.7.3 Recruitment of subjects

A total of 15 subjects were recruited for the pilot study to assess the feasibility of the study protocol. The selection procedure was based on convenience method by selecting the first available BME files submitted for assessment in the month of March 2020.

3.7.4 Pilot procedure and activities

Various procedures were used in the pilot phase to gain more practical method for data collection of the study. The first method included a researcher shadowing Medical Panel or certification committee when assessing BME for diagnosis while parallelly accessing the chest X-rays CAD scores through the web-based server to fill in the questionnaire. A second method included a researcher accessing the diagnosis outcome of the Medical Panel from each BME file after the Medical Panel has completed assessment or certifying the file and extracting CAD scores from the server to fill in the questionnaire. The second method of accessing BME files and extracting CAD scores for filling in the questionnaire was found to be more suitable and practical for data collection compared to the first method. The method was adopted for use to complete the rest of the pilot and for data collection of the study.

3.7.5 Data collection instrument and process during the pilot

A questionnaire which was developed during the proposal development phase was applied in the pilot phase. Data was collected by administering a questionnaire containing of 14 questions to be completed by the researcher. A unique identifier was used to match the chest X-ray image with the Medical Panel findings. The matching produced 100% identical result. All chest X-rays images were anonymised before upload to the CAD software for scoring. The questionnaire consisted of two sections, section A consisting of identification information and socio demographics characteristics. Section B consisting of clinical information further divided into Medical Panel findings and CAD scoring. The questions under Medical Panel findings were all found to be relevant to address key variables important for the study. The questions under the CAD section were found to be unclear in addressing key variable for CAD outcomes. The questions were then corrected to address key variables. The final questionnaire adopted for the study consisted of two section, A with seven questions of socio demographic and section B with seven clinical questionnaires.

3.8 Data collection process in the study

Chest x-rays were accessed from the cloud archive where they are uploaded from the One Stop Clinics in a DICOM (Digital Communication in Medicine) format via the PACS (Picture Archiving System) system. The chest X-rays images were anonymised and transferred to the CAD software's CAD4Silicosis version 1 and CAD4TBv6 through a web link for automatic scoring. The scores outcome was recorded in the study questionnaire. The BME file of each participant was linked with the chest X-ray score. The chest X-rays and the BMEs were assessed by Medical Panel also referred to as certification committee. The Medical Panel or certification committee are a team of four clinicians who hold a minimum qualification of Bachelor of Medicine and Bachelor of Surgery (MBChB) degree specializing in occupational health with over 10 years' experience in the field occupational health. The Medical Panel blinded from the study are certified as B readers by the National Institution for Occupational Safety and health (NIOSH). The outcome of each participant from the Medical Panel assessment were recorded in the questionnaire after the matching with the industry number. The chest X-rays images were also reported by an independent radiologist as a reference standard blinded from the study. The radiologist has over 20 years' experience in diagnosing silicosis and occupational diseases certified with a B reader by NIOSH. The reports of the radiologist and the Medial panel were recorded in the questionnaire.

3.9 Time and cost budget

The study was partly self-funded and additional resources was obtained from the MBOD and Aurum Innova. The duration and cost implication of the study are attached in **appendix 5.**

3.10 Ethics Considerations

The research was approved by the University of Johannesburg: Faculty of Health Sciences Research Ethics Committee (REC) and the Higher Degree Committee (HCD) for ethics clearance **see appendix 2 and 3.**

3.10.1 Access to participants and document record: A permission to access participants BME files in Braamfontein was sought through a written application and approved by the director of the MBOD **see appendix 4.**

3.10.2 Obtaining informed consent: No informed consent was obtained from participants. The study used data from BME files. Access to ex-miners BMEs was approved by the MBOD. Informed consent waiver was sought from the Research Ethics Committee.

3.10.3 Right to equity, human dignity, and protection against harm: All participants were classified as ex-miners and there was no grading of participants according to age or gender. Participants were not be exposed to any form of harm in this research.

3.10.4 Right to anonymity, confidentiality, and privacy: The BME files were accessed in a controlled access room where the Medical Panel seat to do assessment. The questionnaire was completed in the same room. CAD software scoring were conducted in the server room where access is through authorisation. Each participant file was provided with a study unique identity matched to their industry number to allow for matching of results. All data of ex-miners was handled as highly confidential and will not be disclosed to anyone except members of the research team, i.e. researcher and supervisors. The questionnaire and information obtained from the document review are stored under lock and key for a period of five years after which it will be destroyed.

3.10.5 Right to freedom of choice: Participants had the right to withdraw their file from the study at any time and may access information collected through the MBOD.

3.10.6 Right to community and community science: The participants may access any information pertaining to this research and the results of this research through the MBOD following the completion of the study. Dissemination of research findings will include presentations at key meetings, conferences and publications in sources accessed by the population. If any problems exist, that pose a threat to human health, it shall be reported to the MBOD.

3.11 Summary

This chapter described the research design, mapping the study area, target population, associated sampling method and the approaches that were undertaken for the study. It further described inclusion and exclusion criteria for the study. It tested the reliability and validity by applying a pilot study to validate the data collection instrument. It also described the data collection process and the statistical analysis proses. It concluded with ethical considerations.

CHAPTER 4: RESULTS

4.1 Introduction

The aim of this study was to determine the sensitivity and specificity of Computer Aided Detection (CAD) software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa. The **Specific objectives of the study were**

1. To determine the sensitivity and specificity of CAD for detecting silicosis
2. To determine the predictive values of CAD for detecting silicosis
3. To determine likelihood ratios of CAD for detecting silicosis
4. To compare the performance of CAD with the Medical Panel in scoring for silicosis

The sample size for the study was 295 participants. The study received ethics clearance from the University of Johannesburg Research Ethics Committee (REC) and permission to collect data from the Medical Bureau of Occupational Diseases (MBOD). This chapter presents the report of the research findings. The first component reports on descriptive statistics using frequencies and percentages on the dependent and independent variables presented in tables and figures. The other components report on sensitivity and specificity, Predictive values, Likelihood ratios, Receiver Operator Curve (ROC) and Area Under Curve (AUC) for the research questions. The statistical findings are presented in relation to the research question at 95% Confidence Interval (CI). The study had four research questions and hypothesis tested listed below.

The overall research hypothesis was to determine the sensitivity and specificity of CAD software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa.

H_0: CAD software will not sensitively and specifically score chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa.

H_1: CAD software will sensitively and specifically score chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa.

Specific hypothesis was

1. **To determine the predictive values of CAD for detecting silicosis**

H_0: CAD will incorrectly determine positive and negative predictive values for detecting silicosis

H_1: CAD will correctly determine positive and negative predictive values for detecting silicosis

2. **To determine likelihood ratios of CAD for detecting silicosis**

H_0: CAD will incorrectly determine likelihood ratios for detecting silicosis

H_1: CAD will correctly determine likelihood ratios for detecting silicosis

3. **To compare the performance of CAD with the Medical Panel in scoring for silicosis**

H_0: There will be different scoring between CAD and Medical Panel assessment in counting for silicosis

H_1: There will be similar scoring between CAD and Medical Panel assessment in counting for silicosis

4.2 Descriptive statistics

Each participant was allocated with a unique identifier autogenerated by the chest X-rays anonymiser. Data cleaning was conducted checking for duplicates, five duplicates were identified due to error in data entering, the duplicate were cleaned by entering correct values. One missing value of participant age was identified, the value could not be rectified since the participant age was not available on the primary file and the file was excluded from the study. Outlier checks was conducted for CAD4Silicosis scores. No outlier was detected in the dataset. All CAD scores were within normal limits between 0 and 100 shown in figure 4.1.

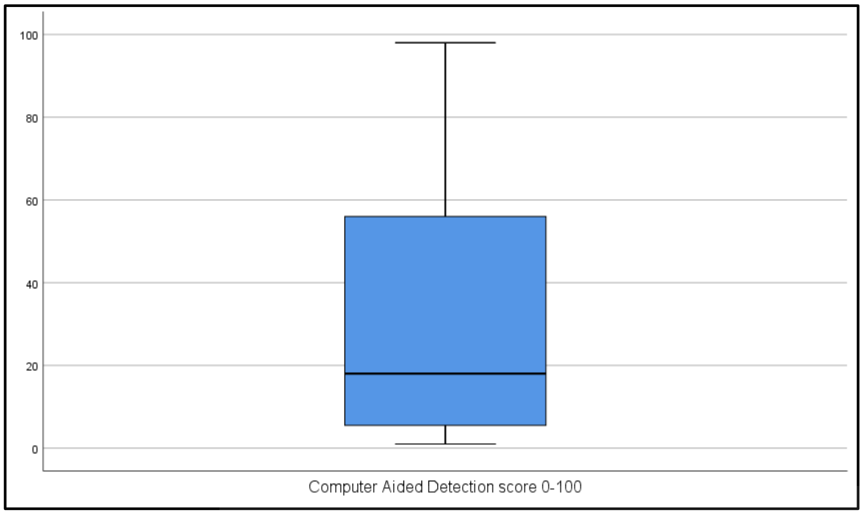


Figure 4.1. CAD4Silicosis outlier

Outlier checks was conducted for CAD4TB scoring. No extreme outlier was detected from the dataset. Three records below the whiskers were within acceptable range of CAD scores between 0 and 100 shown in figure 4.2.

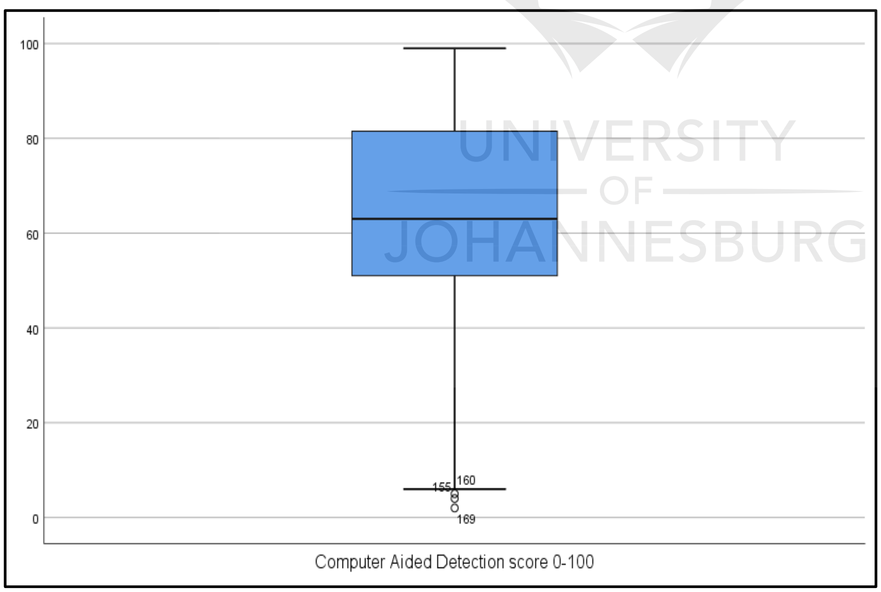


Figure 4.2. CAD4TB outlier

The CAD4Silicosis scores distributions were positively skewed, relatively to normal distribution. The lowest CAD4Silicosis score recorded was 1 and the highest score was 98. The CAD4Silicosis scoring distribution indicates that CAD score of 4 occurred 22 times (7.5%), followed by CAD scores 3 and 5 which occurred 17 times (5.8%), CAD score of 1 occurred 4 times (1.4%) and CAD score of 98 occurred 1 time (0.3%) from the overall scoring distributions shown in figure 4.3.

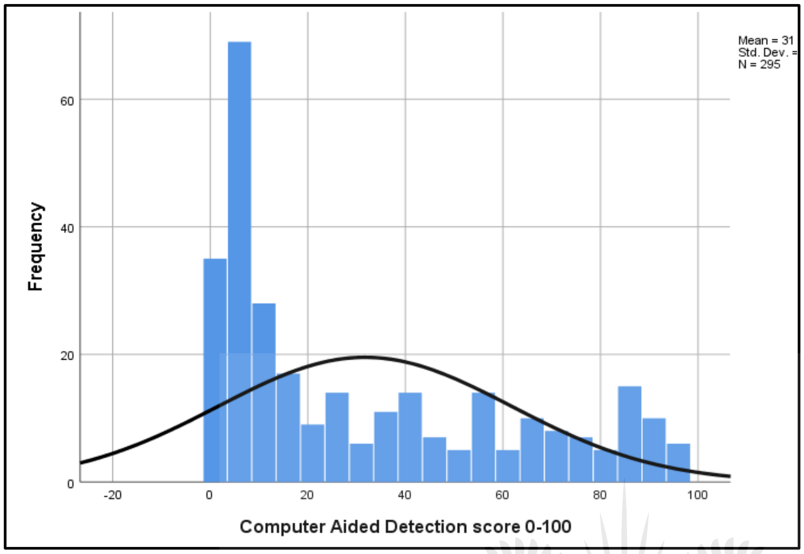


Figure 4.3. CAD4Silicosis scores distributions

The CAD4TB scores distributions were negatively skewed from the normal distribution. The lowest score was 2 and the highest score was 99. Computer aided detection score of 99 occurred 12 time (4.1%), followed by CAD score 48 which occurred 10 times (3.4%) and the rest of the scores were below 2.5% shown in figure 4.4.

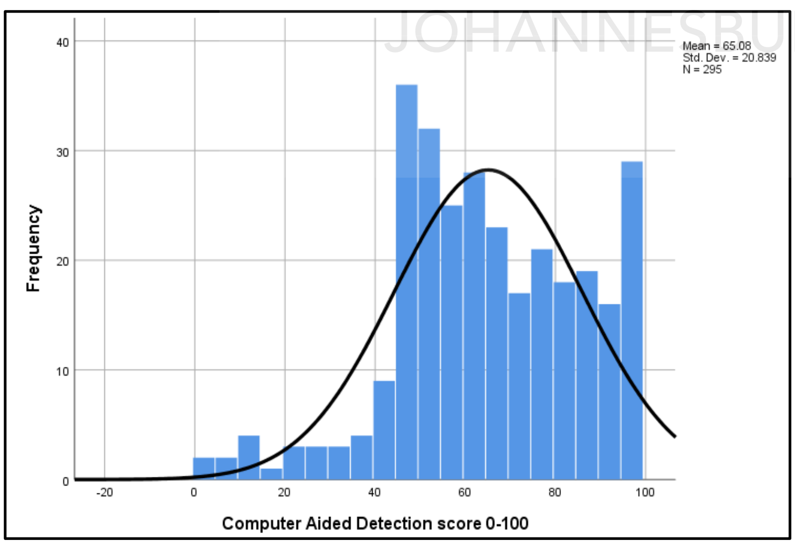


Figure 4.4. CAD4TB score distributions

4.3. Socio-demographic distribution

Table 4.1 show the sociodemographic characteristics of the study participants with associated Medical Panel diagnosis of normal and abnormal findings. The gender composition of the study was 100% male. The age distribution of the participants between 21 – 36 was 1%, between 37-55 was 13.2% and above 55 was 85.4%. The participants age is consistence with elderly population since these since these are retired participants expected to be older. Racial profile was 99.3% of black African and 0.7% of White population. The study included 84.4% of residents from Eastern Cape with 24.4% from the Alice outreach and 60% Bizana Outreach. It also included 15.6% of participants from the North West province, all from the Stillfontein outreach. These is due to the higher proportion ex-miners (one third) estimated to be residing in the Eastern Cape province.

The diagnostic quality of the chest X-rays was of good quality 100%. I performed cross-tabulation to determine Medical Panel diagnosis outcome in relation to sociodemographic characteristics. The Medical Panel diagnosis for the ex-miners based on gender was 50.2% abnormal, the normal diagnosis was 49.8% in all the participants. Medical Panel diagnosis based on age was 0.3% abnormal and 0.7% normal for age between 21 – 36, 4.4% abnormal and 8.8% normal for ages 37 – 55, and 45.5% abnormal and 40% normal for age 56 and above. The Medical Panel diagnosis based on race was 49.2% abnormal and 49.8% normal in black African people, and 0.7% abnormal and 0% normal in white people. The Medical Panel diagnosis based on province was 40.3% abnormal and 44.1% normal in Eastern Cape province (Alice 14.9% abnormal and 9.4% normal, and Bizana outreach 25.4% abnormal and 34.6% normal) and North West was 9.8% abnormal and 5.8% normal all from Stillfontein outreach shown in table 4.1.

Table 4.1: Socio-demographic characteristics of study participants with associated Medical Panel diagnosis of normal and abnormal.

		Total		**Medical Panel Abnormal**		**Medical Panel Normal**	
Characteristics		**n**	**%**	**n**	**%**	**n**	**%**
Gender							
	Male	295	100	148	50.2	147	**49.8**
	Female	0	0				
Age							
	< 21 years	0	0	0	0	0	0
	21 – 36 years	3	1	1	0.3	2	0.7
	37– 55 years	39	13.2	13	4.4	26	8.8
	>56 years	252	85.4	134	45.4	118	40
Race							
	African	293	99.3	146	49.2	147	49.8
	White	2	0.7	2	0.7	0	0
	Coloured	0	0	0		0	0
	Asian	0	0	0		0	0
Province of residence							
	Eastern Cape	249	84.4	119	40.3	130	44.1
	North West	46	15.6	29	9.8	17	5.8
Examination centre							
	Alice Outreach	72	24.4	44	14.9	28	9.4
	Bizana Outreach	177	60.0	75	25.4	102	34.6
	Stillfontein Outreach	46	15.6	29	9.8	17	5.8
Chest X-ray Diagnostic Quality							
	Good quality	295	100	148	50.2	147	49.8
	Poor quality	0	0	0		0	

4.4 Medical Panel diagnosis result

From the 295 subjects, Medical Panel diagnosis was 50.2% (n=148) abnormal and 49.8% (n=147) normal. The Medical Panel diagnosis for silicosis was 32.2% (n=95), Medical Panel diagnosis for TB was 29.2% (n=88) and the Medical Panel diagnosis for combined TB and silicosis was 12.5% (n=38) shown in table 4.2.

Table 4.2: Medical Panel diagnosis positive and negative silicosis, TB, and combined TB and silicosis.

Variable	Medical Panel positive		Medical Panel Negative	
Count and percentage	n	%	n	%
Abnormal and normal diagnosis	148	50.2	147	49.8
Silicosis diagnosis	95	32.2	200	67.8
TB diagnosis	86	29.2	209	70.8
Silicosis and TB diagnosis	37	12.5	258	87.5

4.5 CAD scoring results

Each chest X-ray image got a score from two CAD systems versions namely CAD4silicosis v1 and CAD4TBv6. CAD4Silicosis and CAD4TB produced a scoring between 0 – 100, with 0 score indicative of no abnormality detected and a score of 100 indicative of abnormality detected. A cut-off threshold was determined based on the AUC. Score below the threshold were indicative of no abnormality detected scoring and scores above the threshold were indicative of abnormality detected scoring.

CAD4silicosis scored 44.4% chest X-ray images above the threshold and 55.6% chest X-ray images below the threshold in detecting silicosis when using a cut-off threshold closer to the coordinate points of 25, with scores below 25 labelled below threshold and scores above 25 labelled above threshold shown in table 4.3.

CAD4TB scored 77.7% chest X-ray images above the threshold and 22.7% images below threshold at a cut-off threshold closer to coordinates points of 50, with scores below 50 labelled as scores below threshold and scores above 50 labelled as scores above threshold shown in table 4.3.

Table 4.3: CAD4 Silicosis and CAD4 TB Scoring of Images above the Threshold and Images Below the Threshold at Cut-Off Thresholds Closer to Coordinates Points.

CAD scores	**CAD4silocosis scoring**		**CAD4TB scoring**	
Count and percentage	n	%	n	%
Scores above the threshold	131	44.4	228	77.7
Scores below the threshold	164	55.6	67	22.7

4.6 Results by objective

Objective 1: To determine the sensitivity and specificity of CAD for detecting silicosis.

H_0: CAD software will not sensitively and specifically score chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa

H_1: CAD software will sensitively and specifically score chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa

When calculating sensitivity and specificity at a threshold closer to the coordinates, the sensitivity of CAD4Silisosis for scoring chest X-ray to detect silicosis was 91.6% and the specificity was 78.0%. These results indicate that CAD sensitively scored chest X-rays of ex-miners while compromising specificity shown in table 4.4. We reject the null hypothesis and conclude that CAD software will sensitively score chest X-rays of ex-miners although specificity is compromised. This is statistically significant with a *p* value of .000.

Objective 2: To determine the predictive values of CAD for detecting silicosis.

H_0: CAD will incorrectly determine positive and negative predictive values for detecting silicosis

H_1: CAD will correctly determine positive and negative predictive values for detecting silicosis

CAD4Silicosis scored 87 positive cases of silicosis above the threshold, which were true positive. It further scored 44 negative cases of silicosis above the threshold as positive, these are false positive scoring. CAD4Silicosis scored 156 negative cases of silicosis below the threshold, which were true negative. It further scored 8 positive cases below the threshold as negative, which were positive. These are false negative scoring.

The positive predictive value for CAD4Silicosis to score for silicosis was 66.4% and the negative predictive value for CAD4Silicosis to score for silicosis was 95.1% when compared to Medical Panel. We reject the null hypothesis and conclude that CAD will correctly determine positive and negative predictive values for detecting silicosis shown in table 4.4. This is statistically significant with a *p* value of .000.

Table 4.4: CAD4Silicosis sensitivity, specificity and predictive values for detecting silicosis.

CAD4Silicosis scoring	**Medical Panel silicosis diagnosis**		**P-value**
CAD scores above threshold	Positive for silicosis	Negative for silicosis	
n PPV (Positive Predictive Value) Sensitivity	87 66,40% 91,60%	44 33,60% 22%	.000
CAD scores below threshold n NPV (Negative Predictive Value) Specificity	 8 4,90% 8,40%	 156 95,10% 78%	.000
Total	95	200	

Objective 3: To determine likelihood ratios of CAD for detecting silicosis

H_0: CAD will incorrectly determine likelihood ratios for detecting silicosis

H_1: CAD will correctly determine likelihood ratios for detecting silicosis

Table 4.5 shows that the likelihood radio determines that CAD is sometimes a useful system in predicting the positive silicosis cases in a chest X-ray. However, CAD is a very useful system in predicting the true negative silicosis cases. We reject the null hypothesis and conclude that CAD is a useful system in predicting negative likelihood for silicosis although is sometimes not a very useful system in predicting positive likelihood for silicosis.

Table 4.5: CAD4Silicosis likelihood ratios for detecting silicosis.

CAD4Silicosis scoring	**Medical Panel silicosis diagnosis**		**P-value**
CAD4Silicosis scoring	Positive for silicosis	Negative for silicosis	
Likelihood ration	4.1	0.1	.000

4.7 CAD4TB scoring distribution

CAD4TB scored 85 positive cases of TB above the threshold, which were true positive. It further scored 143 negative cases of TB above the threshold which were negative; these were false positive scoring. CAD4TB scored 66 negative cases of TB cases below the threshold, which were true negative. It further scored 1 positive case of TB below the threshold which was positive; this was a false negative case. This is statistically significant with a *p* value of 0.0001.

When calculating sensitivity and specificity at a threshold closer to the coordinates, the sensitivity of CAD4TB for scoring chest X-ray to detect TB was 98,8% and the specificity was 31.6%. The positive predictive value for CAD to score for TB was 37,3% and the negative predictive value for CAD to score for TB was 98,5% when compared to Medical Panel diagnosis shown in Table 4.6.

Table 4.6: CAD4TB sensitivity, specificity and predictive values for detecting TB.

CAD4TB scoring	**Medical Panel TB diagnosis**		**P-value**
CAD scores above threshold	Positive for TB	Negative for TB	
n PPV (Positive Predictive Value) Sensitivity	85 37,30% 98,80%	143 62,7% 68.4%	.000
CAD scores below threshold n NPV (Negative Predictive Value) Specificity	 1 1.5% 1.2%	 66 98.5% 31.6%	.000
Total	86	209	

4.8 Receiver Operator Curve (ROC)

Receiver Operator Curve (ROC) curve is a graph used to demonstrate the performance of a binary classifier. The Area Under Curve (AUC) is the best way to summarise its performance to a single number.

This curve plays a vital role in evaluating diagnostic ability of CAD to discriminate between true positives and true negatives at an optimal cut-off value. The closer the diagonal line is to the upper top left of the graph, the better the performance of the system. The ROC curves for CAD4Silicosis and CAD4TBv6 were all above the diagonal line.

Objective 4: To compare the performance of CAD with the Medical Panel in scoring for silicosis

> H_0: There will be different scoring between CAD and Medical Panel assessment in counting for silicosis.
> H_1: There will be similar scoring between CAD and Medical Panel assessment in counting for silicosis.

When using CAD4Silicosis to score for all abnormal and normal in the chest X-ray inclusive of silicosis, TB, combined TB and Silicosis and other abnormalities, the systems produced good result with an AUC of .886 (95% CI 0.848 - 0.923) compared to Medical Panel. This is statistically significant with a *p* value of .000 with a standard error of 0.019 shown in figure 4.5. We reject the null hypothesis and conclude that CAD produced a good AUC scoring when compared to Medical Panel.

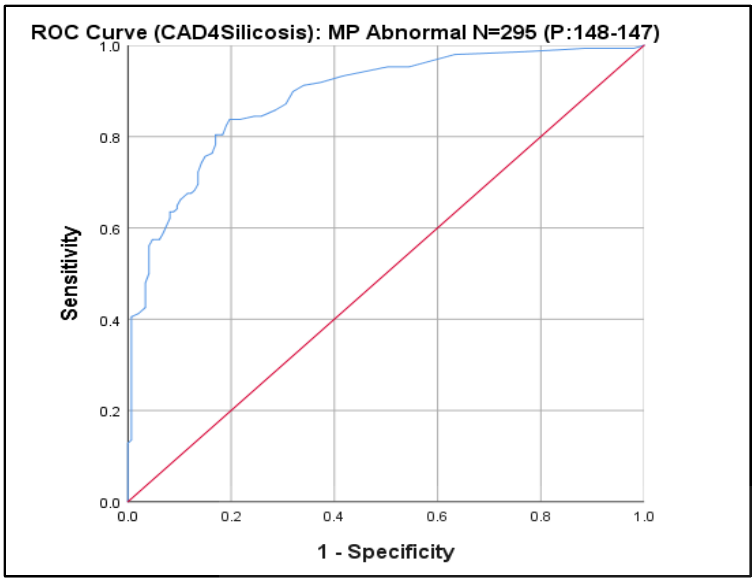


Figure 4.5. ROC, Sensitivity and Specificity of CAD4Silicosis for discriminating abnormal and normal compared to medical panel

CAD4TBv6 produced an AUC of .889 (95%, CI 0.850 – 0.927) when scoring for abnormal and normal compared to Medical Panel. This is statistically significant with a *p* value of .000 and a standard error of .020 shown in figure 4.6. We reject the null hypothesis and conclude that CAD produced a good AUC scoring when compared to Medical Panel.

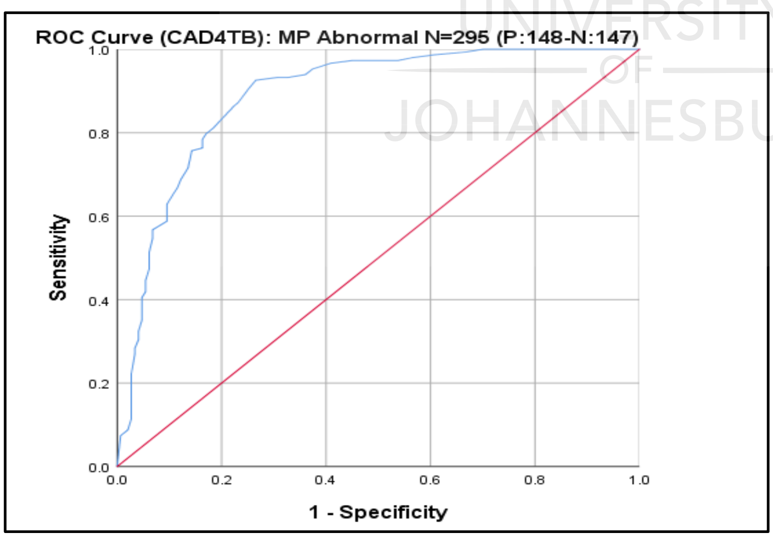


Figure 4.6. ROC, Sensitivity and Specificity of CAD4TBv6 for discriminating abnormal and normal compared to medical panel.

When CAD4Silicosis was used to score for silicosis to detect silicosis compared to Medical Panel, the AUC was 0.918 (95%, CI 0.887 – 0.949). This is statistic significant with a *p* value of .000 shown in figure 4.7. We reject the null hypothesis and conclude that CAD produced a great AUC scoring when compared to Medical Panel in scoring for silicosis.

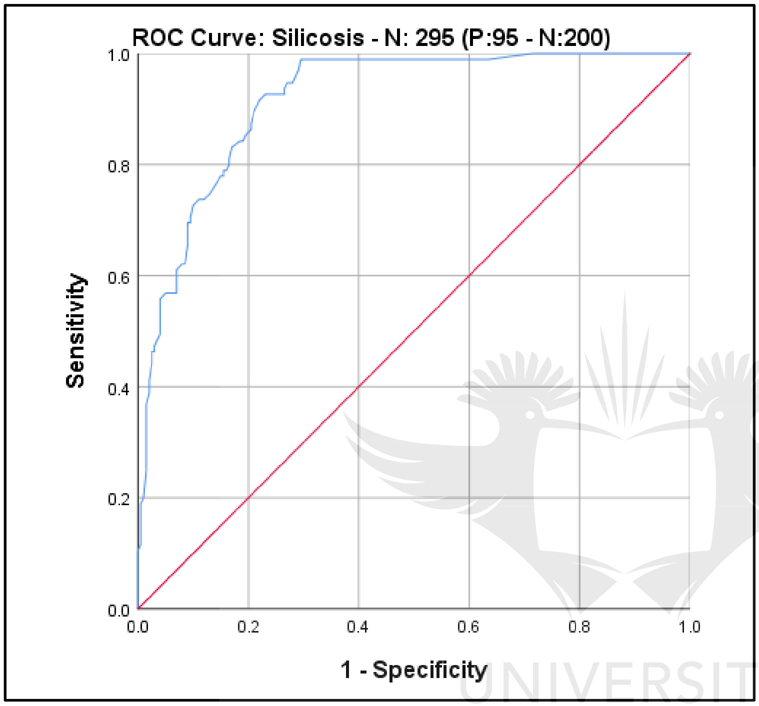


Figure 4.7. ROC, Sensitivity and Specificity of CAD4Silicosis for detecting Silicosis compared to medical panel.

When CAD4Silicosis was used to score for the presence of combined silicosis and TB to detect silico-TB compared to Medical Panel, the AUC was 0.802 (95%, CI 0.749 – 0.855). This is statistic significant with a *p* value of .000 shown in figure 4.8. We reject the null hypothesis and conclude that CAD produced a good AUC scoring for combined silicosis and TB when compared to Medical Panel when scoring for combined silicosis and TB.

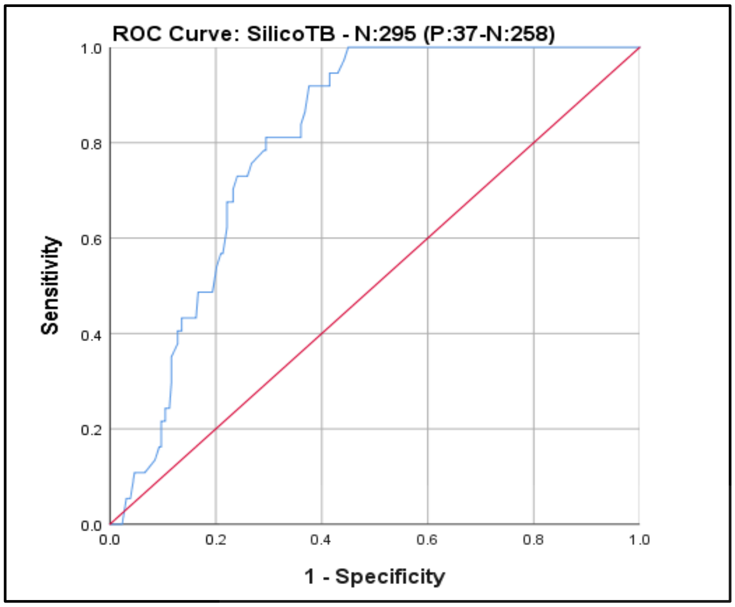


Figure 4.8. ROC, Sensitivity and Specificity of CAD4Silicosus for discriminating Silico-TB compared to Medical Panel.

When CAD4TBv6 was used to score for TB compared to Medical Panel, the AUC was .826 (95% CI, 0.780 – 0.873). This is statistically significant with a *p* value of .000 shown in figure 4.9. CAD produced a good AUC scoring when compared to Medical Panel.

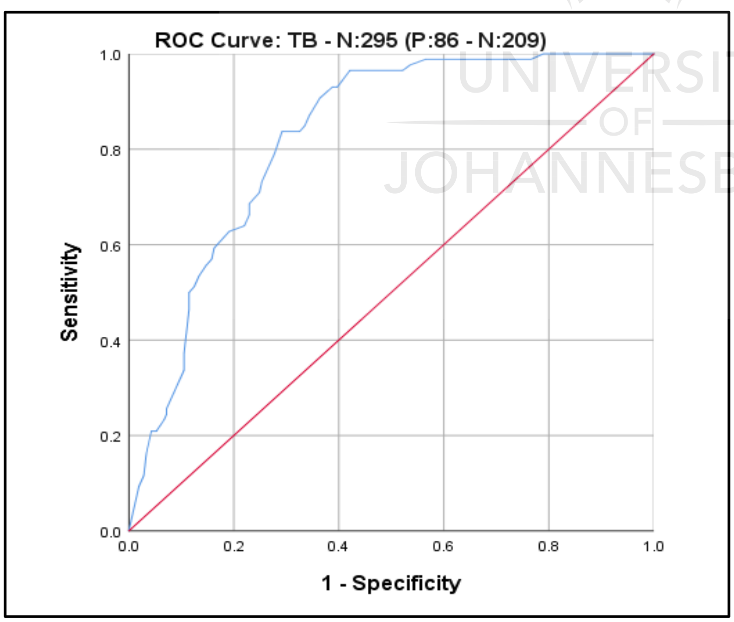


Figure 4.9 ROC, Sensitivity and Specificity of CAD4TBv6 for detecting TB compared to Medical Panel.

4.9 Summary

This chapter report on results for the study which detail the use of CAD4Silicosis version 1 and CAD4TBv6 for scoring each chest X-ray image compared to Medical Panel. A sample of 295 ex-miner were collected. The chest X-rays images were anonymised using a chest X-ray anonymiser software. The chapter further detailed the data cleaning process by checking for duplicates, outliers, missing values and CAD scores distributions using descriptive statistics. I reported on sociodemographic characteristics to determine the characteristics of the participants, with a gender distribution of 100% male dominated by elderly population of black African race from Eastern Cape and North West. Medical Panel scoring distribution was conducted with 50.2% abnormal diagnosis. Analysis by objective was shown using CAD scoring distribution. Sensitivity and specificity of the CAD scoring from the two CAD systems were determined using the AUC, a 2x2 table and the ROC curve. Predictive values were determined for both the CAD systems. Likelihood ration for CAD4Silicosis was calculated. Medical Panel diagnosis and CAD scoring were compared by using ROC and AUC.

CHAPTER 5: DISCUSSION

5.1 Introduction

Silicosis is one of the occupational diseases which increases with the duration of exposure to silica dust that has been a major problem for ex-miners (Fernandez *et al.,* 2015). Chest radiograph is an important tool for diagnosing silicosis of ex-miners (Williams, 2006). Ex-miners have been at high risk of exposure to silica dust putting them in high risk of developing prolonged respiratory diseases such as silicosis, TB and other occupational diseases (Mokwena, 2018).

The purpose of the study was to determine the sensitivity and specificity of computer aided detection (CAD) software for scoring chest X-rays of ex-miners compared to Medical Panel in Johannesburg, South Africa. This chapter provides a detailed interpretation and discussion of the study findings. In details, sociodemographic characteristics, Medical Panel diagnosis and CAD scoring are interpreted and discussed. This chapter summarise the discussion, then end with conclusions, recommendations, strength and weaknesses.

5.2 Interpretation of findings and discussion

5.2.1 Sociodemographic findings

This is one of the first few studies in South Africa to report the performance of CAD4Silisosis and CAD4TBv6 systems for detecting silicosis and TB in ex-miner's population in a high TB burden and high silicosis prevalence settings. The Medical Panel diagnosis for the ex-miners based on gender from all the male participants was 50.2% abnormal, the normal diagnosis was 49.8%, no female participant was recorded. This was not surprising because it is submitted that males are dominant in the mining industry due to the nature of activities performed in the mining industry. These findings further demonstrate that at least one in two ex-miners has chest or lungs problems. These findings are consistent with previous findings from Naidoo (2013) who reported that the prevalence rate of occupational lung diseases (Pneumoconiosis) in ex-miners are ranging from 26% to 36%.

Medical Panel diagnosis based on age was 0.3% abnormal and 0.7% normal for age between 21 – 36, Medical Panel abnormal was 4.4% abnormal and 8.8% normal diagnosis for age 37 – 55, and Medical Panel diagnosis for age above 56 was 45.5% abnormal and 40% normal. These findings are not surprising since all the participants in the study are ex-miners retired from the mines due to illness or having left mine due to retirement age or retracement. These findings are similar to Bloch *et al.,* (2018) who found highest mortality rate of people who left the mines to be at the age of >45 years. The Medical Panel diagnosis based on race was 49.2% abnormal and 49.8% normal in black African people, and 0.7% abnormal and 0% normal in white people. Similar findings were noted from previous studies that reported that the mining industry has been a central feature of employment for black gold mineworkers in South Africa since the inception of mining over the past century (Roberts, 2009). These was also expected since the mining industry was dominated by black Africans population who worked underground where the risk of exposure to silica dust is high.

The Medical Panel diagnosis based on province was 40.3% abnormal and 44.1% normal from Eastern Cape province (Alice outreach 14.9% abnormal and 9.4% normal, and Bizana outreach 25.4% abnormal and 34.6% normal) and from North West Stillfontein outreach was 9.8% abnormal and 5.8% normal. These findings are similar with previous findings Roberts (2009) who found that the Eastern Cape province previously known as Transkei has been the major labour sending province for South African mining industry for over centuries.

5.1.2 Medical Panel diagnosis for silicosis- result

The Medical Panel diagnosis for silicosis was 32.2% (n=95), these findings are consistent with previous findings which reported that the prevalence of silicosis amongst goldminers is estimates to be 18.3 – 19.9% in South Africa (Churchyard *et al.*, 2015). Medical Panel diagnosis for TB was 29.2% (n=88) and the Medical Panel diagnosis for combined TB and silicosis was 12.5% (n=37). This finding is consistent with previous studies which found that the prevalence of TB rate in South Africa amongst the mining workforce is estimated to be 2500 to 3000 cases per 100 000 (World Bank, 2017).

5.1.3 CAD scoring

A perfect CAD system will produce positive scoring for all the chest X-ray images which have occupational lung diseases. Its ability to score all the positive is described as sensitivity. However, a high sensitivity alone does not make the CAD system great, a great CAD also needs to detect all negative cases as negative expressed as specificity (van Stralen *et al.*, 2009). A great CAD system will produce sensitivity and specificity of 90% and above, a good CAD system will produce a sensitivity and specificity from 80% to 89%. A fair CAD system produce a sensitivity and specificity from 70% to 79% and a poor system produce sensitivity and specificity under 60% (van Stralen *et al.,* 2009).

In this study the sensitivity and specificity were calculated. Out of 295 ex-miners who participated in the study, 95 of them had diagnosis of silicosis by the Medical Panel from the chest X-rays, CAD4Silicosis produced a sensitivity of 91.6%, 200 participants had no silicosis detected from the chest X-rays by the Medical Panel, CAD4Silicosis produced a specificity of 78%. These results indicate that CAD produced a great sensitivity for scoring for silicosis in the chest X-rays of ex-miners when compared to Medical Panel.

From the 295 participants, 86 of them had TB and 209 of them did not have TB detected by the Medical Panel. CAD4TB produced a sensitivity of 98.8% and specificity of 31.6% when scoring for TB. This result indicates a great performance by CAD in scoring for positive TB. However, specificity is compromised. These findings are consistent with a review by Khan *et al* (2017) on available CAD system found that evidence currently available from the literature suggest that CAD system can achieve high sensitivity of 85% plus, although specificity is as low as ranging between 23% to 69%.

Receiver Operating Characteristic (ROC) curve is a graph used to demonstrate the performance of a binary classifier. The Area Under Curve (AUC) is the best way to summarise its performance to a single number.

CAD4Silicosis produced a great AUC of 0.918 (95%, CI 0.887 – 0.949) when used to score for silicosis to detect silicosis compared to Medical Panel. These results are similar to Young *et al.*, (2020) who found that when using CAD systems to score for silicosis the CAD systems produced an AUC ranging from 0.986, 95% CI 0.960-10.0 to 0.939, +95%CI 0.901-0.978. CAD4Silicosis produced good AUC of 0.802 (95%, CI 0.749 – 0.855) when scoring for combined silicosis and TB. CAD4TB produced good AUC of 0.826 (95% CI, 0.780 – 0.873) when scoring for TB compared to Medical Panel. These results indicate a good performance by CAD4Silicosis in detecting combined TB and silicosis. The study adds new findings which differ from Young *et al.*, *(*2020) who found that three CAD systems decreased in performance when scoring for a combined TB and silicosis.

These findings demonstrate that the CAD systems performed well across the scoring of silicosis, TB and silico-TB when compared to Medical Panel differentiating between chest X-rays with silicosis, TB and silico-TB. As such this study adds new findings from previous studies which demonstrate that CAD system can accurately score silicosis, combined silicosis and TB.

The positive predictive value indicates the probability of ex-miners having the diseases after a positive diagnosis and the negative predictive value indicate the probability of the ex-miner not having the disease after a negative diagnosis by the Medical Panel. The positive predictive value for CAD4Silicosis to score for silicosis was 66.4% and the negative predictive value for CAD4Silicosis to score for silicosis was 95.1% when compared to Medical Panel. The positive predictive value for CAD4TB to score for TB was 37,3% and the negative predictive value for CAD to score for TB was 98,5% when compared to Medical Panel diagnosis. The negative predictive values of this study was higher, and these findings are similar to findings shown in Muyoyeta *et al.*, (2014) who found the sensitivity and the negative predictive value to be high with the positive predictive value to be low when comparing CAD with Xpert for detecting TB, with both studies having used automated reading by CAD systems.

5.3 Summary outcome

The CAD systems performed well in both silicosis and TB scoring. The sensitivity and the negative predictive value of CAD4Silicosis when scoring for silicosis were higher. This study adds findings from previous literature which demonstrated that CAD systems can accurately detect TB and normal. Our findings demonstrate that CAD4Silicosis can accurately detect silicosis and normal chest X-rays images. These findings were similar to a study by Young *et al.,* (2020) in a review of four CAD systems who found two CAD systems to have accurately differentiated between silicosis and normal chest X-rays images.

Furthermore, our finding demonstrates for the first time that CAD can detect combined silicosis and TB. CAD4TBv6 achieved good AUC when scoring for TB. These findings demonstrate the versatility of CAD systems to detect different diseases when validated for those specific diseases. However, each chest X-rays image produced two different scores for each CAD module. These further demonstrate that CAD can be validated to produce scoring for different diseases from one chest X-ray image if the image is analysed by that system. These findings further indicate that CAD system can be used as a tool to assists in detecting of silicosis TB, and silico-TB.

5.4 Conclusions

Computer aided detection systems performed well across the scoring of silicosis and silico-TB when compared to human readers in differentiating between people with TB, silicosis and silico-TB. This performance is in line with the principle of CAD systems that performance will improve when additional training material are provided for further validation. These systems therefore have the potential to improve silicosis, silico-TB, and TB diagnosis to enhance capacity in resources constrained environmental settings. Computer aided detection has the potential to improve efficiency as a supporting diagnostic tool. There is a potential to roll out CAD systems in high burden TB and Silicosis settings.

5.5 Strength and Limitations

The major limitations of the study are that we used human reader Medical Panel and radiologist as a reference standard for diagnosis of silicosis, silico-TB and TB. The best option would have been to use additional information such as environmental exposure history, GeneXpert results, lung functions result and occupational health practitioner assessment report. However, the Medical Panel reach a conclusive diagnosis in consideration of other factors such as environmental exposure, history of working underground, medical assessment, lung function result, previous and current medical history, TB treatment history and X-pert diagnosis but we did not include this information for this study. Another limitation is that inter-examiner reliability for Medical Panel was not determined.

5.6 Recommendations

Based on the findings of this study, the following recommendations are proffered:

1. The MBOD should consider adopting the CAD systems to help reduce labour and increase rates of timely and accurate diagnosis. The CAD systems can complement the existing Medical Panel approach and the radiologist.

2. The MBOD is encouraged to invest in further studies including providing data that can be used to train the CAD to improve its levels of sensitivity and specificity in detecting occupational lung diseases.

Further evidence is needed to guide the use of CAD in detecting other occupational lung diseases such as obstructive air way disease. Environmental exposure information of history of working underground, medical assessment, lung function result, previous and current medical history, TB treatment history and sputum result / X-pert diagnosis should be considered for inclusion in further studies.

5.7 Public health implications

The study helps to provide an answer on the future use of CAD in occupational health especially in the mining sector. It will further influence the scope of practice and algorithm for detecting silicosis in the country. It further adds benefit for detection of silicosis in population at high risk of exposure to occupational hazards saving lives and resources.

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Appendix 1 Questionnaire

Section A

Section A	
Sociodemographic	
Age	
Gender	Male: 1 Female: 2
Race	Black: 1 White: 2 Coloured: 3 Asian: 4
Province	
Examination centre	
Section B	
Clinical information	
Is the chest X-ray image of diagnostic quality?	Yes: 1 No: 2
Medical Panel Diagnosis / Radiologist	
Is the chest x-ray image abnormal?	Positive: 1 Negative: 2
Does the chest x-ray have silicosis?	Positive: 1 Negative: 2
Does the chest x-ray have TB?	Positive: 1 Negative: 2

Does the chest x-ray have silico tuberculosis?	Positive: 1 Negative: 2
Computer Aided Detection Scoring	
What is the CAD4Silicosis score for the chest x-ray image?	
What is the CAD4TB score for the chest x-ray image?	

Appendix 2 HDC approval

FACULTY OF HEALTH SCIENCES
HIGHER DEGREES COMMITTEE

07 February 2020

TO WHOM IT MAY CONCERN:

Student:	**MOROPANE, K**
Student Number:	**820301307**

TITLE OF RESEARCH PROPOSAL:	Sensitivity and specificity of Computer Aided Detection for scoring chest X-rays compared with Medical Panel in Johannesburg, South Africa
DEPARTMENT OR PROGRAMME:	**MASTER OF PUBLIC HEALTH**

SUPERVISOR: **Prof S Feresu** **CO-SUPERVISOR:** **Dr LR Kuonza**

The Faculty Higher Degrees Committee has scrutinised your research proposal and confirms that it complies with the approved research standards of the Faculty of Health Sciences; University of Johannesburg.

The proposal has been awarded a Code 2A – Approved with suggestions, without re-submission. Attached recommendations were made by the Committee which will add value to your proposal.

Please make these amendments to the satisfaction of your supervisor/s and submit a corrected copy of the proposal to the Faculty Research Administrator after which your clearance number will be issued.

The HDC would like to extend their best wishes to you with your postgraduate studies.

Yours sincerely,

Prof S Nalla

Chair: Faculty of Health Sciences HDC

Tel: 011 559 6258

Email: shahedn@uj.ac.za

Appendix 3 Ethical approval

FACULTY OF HEALTH SCIENCES
RESEARCH ETHICS COMMITTEE

NHREC Registration: REC 241112-035

ETHICAL CLEARANCE LETTER
(RECX 2.0)

Student/Researcher Name	Kgaugelo Moropane	Student Number	820301307
Supervisor Name	Feresu, Shingairai		
Department	Environmental Health		
Research Title	SENSITIVITY AND SPECIFICITY OF COMPUTER AIDED DETECTION FOR SCORING CHEST X-RAYS COMPARED WITH MEDICAL PANEL IN JOHANNESBURG, SOUTH AFRICA		
Date	02 March 2020	Clearance Number	**REC-345-2020**

Approval of the research proposal with details given above is granted, subject to any conditions under 1 below, and is valid until 2021/03/01.

1. Conditions:
None.

2. Renewal:
It is required that this ethical clearance is renewed annually, within two weeks of the date indicated above. Renewal must be done using the Ethical Clearance Renewal Form (REC 10.0), to be completed and submitted to the Faculty Administration office. *See Section 12 of the REC Standard Operating Procedures.*

3. Amendments:
Any envisaged amendments to the research proposal that has been granted ethical clearance must be submitted to the REC using the Research Proposal Amendment Application Form (REC 8.0) prior to the research being amended. Amendments to research may only be carried out once a new ethical clearance letter is issued. *See Section 13 of the REC Standard Operating Procedures.*

4. Adverse Events, Deviations or Non-compliance:
Adverse events, research proposal deviations or non-compliance must be reported within the stipulated time-frames using the Adverse Event Reporting Form (REC 9.0). *See Section 14 of the REC Standard Operating Procedures.*

The REC wishes you all the best for your studies.

Yours sincerely.

Prof. Christopher Stein
Chairperson: REC
Tel: 011 559 6564
Email: cstein@uj.ac.za

Appendix 4: Data collection approval

health
Department:
Health
REPUBLIC OF SOUTH AFRICA

Medical Bureau of Occupational Diseases (MBOD)

Department of Health

144 De Korte Street

Johannesburg

23/06/2020

Ref: Kgaugelo Moropane

ID: 8405265316086

Student number: 820301307

Subject: Permission for data collection

To whom it may concern

This letter serves as a confirmation for granting permission to conduct a research study titled **"Sensitivity and specificity of Computer Aided Detection for scoring chest X-rays compared with Medical Panel in Johannesburg, South Africa"**. All data collected for the research must be kept anonymous. Data collection for the study will involve the collection of secondary data from medical files with minimal human contact. All protocols and procedures must be adhered to during the data collection period.

Yours sincerely

Dr J. Mtshali

DEPT. VAN GESONDHEID
MBOD
P.O. BOX 4584
2020 -06- 25
JOHANNESBURG 2000
DEPT. OF HEALTH

Appendix 5: Timeframe

	Task	Assigned To	Start	End	Dur
	Project Summary		2/9/19	16/7/20	222
1	Proposal witting	Moropane	2/9/19	29/9/19	20
2	Ethical consideration, validity and reliability	Moropane	30/9/19	13/10/19	10
3	Pilot data collection tool	Moropane	21/10/19	27/10/19	5
4	Ethics submission for high degree and approval	Moropane	28/10/19	8/12/19	30
5	Data collection, capturing, data analysis and interpretation	Moropane	13/1/20	1/3/20	35
6	Report witting, correction with supervisor	Moropane and Prof Feresu	9/3/20	26/4/20	33
7	Final submission and presentation of results	Moropane and Prof Feresu	4/5/20	21/6/20	34
8	Results	Moropane and Prof Feresu	29/6/20	16/7/20	14

2019: Sep Oct Nov Dec
2020: Jan Feb Mar Apr May Jun Jul

Appendix 6: Cost and budget

Item	Quantities of items	Cost per item	Total cost
Travel to field data collection site	6	R 100,00	R 600,00
Personnel hire	3	R 875,00	R 2 625,00
CAD software per image	295	R 12,00	R 3 540,00
Stationery	1	R 500,00	R 500,00
Editing of report and statistics analysis	1	R 4 500,00	R 4 500,00
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Appendix 7: Editor Certificate

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To whom it may concern

Tis serves to certify that I **Dr. Thenjiwe Sisimayi (Ph.D.)** have proofread and/or edited **Kgaugelo Moropane** 's Masters Dissertation to ensure that the language, grammar, punctuation and spelling are academically sound and appropriate, by rectifying errors, wherever these have been identified, and rephrasing sentences that would possibly make one lose sight of the flow of the argument.

Title of the Dissertation:	**Sensitivity and specificity of Computer Aided Detection for scoring chest X-rays compared with Medical Panel in Johannesburg, South Africa**
Editor's name:	**Dr. Thenjiwe Sisimayi (Ph.D.)**
Qualification:	**PH.D. in Public Health**
Signature:	
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Appendix 8: Turnitin Certificate

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UNIVERSITY OF JOHANNESBURG

A research proposal presented to the

Faculty of Health Sciences,

University of Johannesburg,

In partial fulfilment of Master of Public Health

By

Kgaugelo Moropane

(Student number: 820301307)

Supervisor:

Prof Shingairai A Feresu **Date: 24/01/2021**

Co-Supervisor:

Dr Lazarus R Kuonza **Date: 24/01/2021**

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